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Difference in temporal variation of temperature-related mortality risk in seven major South Korean cities spanning 1998–2013

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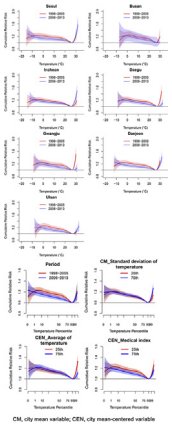
HIGHLIGHTS

- Temporal variation in temperature-mortality relationship differed across cities.
- Heat effect decreased from 1998–2005 to 2006–2013 in cities with higher average temperature.
- In cities with lower average temperature, heat effect did not decrease.
- Change in heat effect was negatively associated with change in average temperature.
- Moderate cold effect decreased while medical resources improved over time.

GRAPHICAL ABSTRACT



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ABSTRACT

Temporal variation of temperature-related mortality risk is an important issue in climate change era. However, difference in this temporal variation across cities in South Korea remains unclear. The aim of this study was to explore whether temporal variation might differ spatially across seven metropolitan cities of Korea during the period of 1998–2013. We estimated cumulative associations between temperature (up to previous 14 days of exposure) and all-cause mortality, and compared cumulative associations between the first eight years (1998–2005) and the last eight years (2006–2013). Multivariate meta-regression analysis was performed to investigate what factors might be associated with spatial and temporal variation in cumulative associations. We found that Busan, Daegu, and Gwangju experienced decrease in heat effect from 1998–2005 to 2006–2013, while Incheon experienced increase in heat effect. By comparing mortality risk at 99th percentile of temperature to mortality risk at minimum mortality temperature, percentage increase of mortality risk changed from 4.8% (95% CI: −1.3, 11.3) to 0.4% (95% CI: −6.0, 7.4) in Busan, from 17.2% (95% CI: 10.2, 24.7) to 4.0% (95% CI: −1.4, 9.8) in Daegu, from 20.3% (95% CI: 11.5, 29.7) to 2.2% (95% CI: −3.5, 8.3) in Gwangju, and from 3.5% (95% CI: 0.2, 6.8) to 7.9% (95% CI: 5.0, 10.9) in Incheon, respectively. Change in average temperature from 1998–2005 to 2006–2013 was negatively associated with change in heat effect even though average temperature in most of the cities fluctuated over time. We also found that all seven cities had decrease in effect of moderate cold temperature from 1998–2005 to 2006–2013. Such decrease was associated with improvement in medical resources.

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Results of this study suggest that plans for adaptation to temperature-related risks should differ across populations because adaptation to temperature varies across populations and within the same population over different time.

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1. Introduction

According to Intergovernmental Panel on Climate Change 5th synthesis report (Pachauri et al., 2014), the frequency and intensity of heat waves are expected to increase while those of cold days are expected to decrease in the future. To formulate efficient policies to address health effects of climate change, understanding relationships between temperature and health end-points is crucial.

Temperature-mortality relationship and its heterogeneity across cities and countries have been well documented (Gasparrini et al., 2015b; Guo et al., 2016; Hajat and Kosatky, 2010; Leone et al., 2013; McGeehin and Mirabelli, 2001; McMichael et al., 2008; Medina-Ramón and Schwartz, 2007). Temporal variation in such relationship has been emphasized due to its public health importance for adaptation to climate change. It is believed that increased prevalence of air conditioning, better conditions in housing, introduction of heat wave warning systems, improved medical resources and socioeconomic resources have contributed to decrease in mortality effects of extreme temperature, particularly, extreme heat (Arbuthnott et al., 2016; Sheridan and Allen, 2018).

South Korea is no exception to climate change. By the end of the 21st century, temperature in South Korea is projected to increase by 3 °C based on Representative Concentration Pathway (RCP) 4.5 and 5.7 °C based on RCP 8.5 (KMA, 2014). Temporal variation in the temperature-mortality relationship in South Korea has been reported in several studies with conflicting results. The discrepancy may be due to difference in study periods, study populations, and statistical methods. Gasparrini et al. (2015a) have shown that temporal variations in effect of heat on mortality over 11 days of exposure during summer (i.e., slope in the temperature-mortality relationship) differ across countries. Such effect has decreased over time in the United States, Japan, and Spain, but not in South Korea. Their study included seven major South Korean cities during the period of 1992–2010. On the contrary, two studies for the period of 1992–2010 found decreasing patterns in heat effect over 2 days of exposure in six major cities (Chung et al., 2017) or over 10 days of exposure in seven major cities (Lee et al., 2018b). Meanwhile, a study for Seoul, the capital city of South Korea, during the period of 1995–2011 showed that temporal variation in the heat effect over 22 days of the exposure varied by cause-specific mortality (Kim et al., 2015). Heo et al. (2016) have compared heat effect nationwide for 1996–2000 and for 2008–2012, and found that temporal variation in heat effect varied by regional climate. For cold effect, one study did not find temporal change in cold effect over eight days of exposure in six cities during the period of 1992–2010 (Chung et al., 2017). In contrast, other study found an increasing pattern of cold effect over 22 days of exposure in Seoul during the period of 1995–2011 (Kim et al., 2015). In other words, temporal variation (and spatial variation of this variation) in the temperature-mortality relationship need(s) to be clarified.

Populations are likely to experience unequal mortality effects of temperature since they live in different city environments such as regional climates and socio-economic inequalities (Anderson and Bell, 2009; Browning et al., 2006; Harlan et al., 2013; Healy, 2003; Huang et al., 2015; Kim and Kim, 2017; O'Neill et al., 2005). We hypothesized that temporal variation in temperature effect might vary spatially in South Korea. This hypothesis implies that inequality of temperature effect across cities may diminish or deepen over time. Identifying difference in such temporal variation and factors associated with this variation would be important to estimate future burden of climate change, and tackle unequal health effects of climate change (McMichael et al., 2006).

Therefore, this study aimed to explore spatiotemporal variation in the effect of heat and cold temperature on mortality in seven major cities of South Korea spanning 1998–2013. This study also aimed to identify factors associated with such variation.

2. Methods

We used dataset for seven major cities of South Korea during the period of 1998–2013. Information for this dataset has been described previously (Kim et al., 2017). Variables of this dataset used in this study included daily cases of all-cause mortality (International Classification of Diseases-10th revision, A00-R99), cardiopulmonary mortality (I00-J99), cardiovascular mortality (I00-99) and respiratory mortality (J00-99). Daily mean ambient temperature and relative humidity were calculated using hourly measured values from a single monitoring station situated in the center of a city. We separated this dataset into two 8-year datasets: 1998–2005 and 2006–2013. The National Emergency Management (NEM) established comprehensive plans for tackling heat wave in 2005. These plans include development of heat wave warning and surveillance system and dissemination of individual measures to avoid heat stress.

In the first stage of analysis, we performed time-stratified case-crossover analyses for each of the seven cities. Calendar month was matched (i.e. year and month were matched). For ease of computation, we used conditional Poisson regression (Armstrong et al., 2014). Over-dispersion was considered. To allow a lag-structure of temperature, we applied distributed lag non-linear models (DLNM). Cross-basis for temperature was used to consider its non-linear relationship with mortality and its non-linear lag-response relationship (Gasparrini et al., 2010). For its non-linear relationship with mortality, we used a B-spline with second degree and knots in 10th, 50th, and 90th percentile of temperature. For its non-linear lag-response relationship, we used a natural cubic spline with five degrees of freedom for equally spaced knots in logarithm scale. Lag length was considered up to 14, 21, and 28 days, since previous studies on the same cities showed that these lag lengths were required to capture heat and cold effect on mortality including mortality displacement (Guo et al., 2016; Kim et al., 2017). Day of the week and holidays was adjusted using dummy variables. Relative humidity was adjusted using natural cubic spline with 3 degree of freedoms (dfs). We estimated city-specific associations of lag-structure of temperature with all-cause mortality and cardiopulmonary mortality in 1998–2005 and 2006–2013 dataset respectively.

In the second stage of analysis, we fitted multivariate meta-regression models (Gasparrini et al., 2012) with city and time period-specific characteristic variables. Since DLNM is high-dimensional, we reduced the number of parameters, obtained summary estimates for cumulative associations between temperature and mortality, and used these summary estimates in multivariate meta-regression. (Gasparrini and Armstrong, 2013). City characteristic variables included average of daily mean temperature, standard deviation of daily mean temperature, gross regional domestic products per capita (GRDP), the prevalence of air conditioning, the proportion of those aged 65 years or older, population density, and a medical index. Since average values of daily mean temperature and standard deviation of daily mean temperature were highly correlated with latitude and longitude, we excluded latitude and longitude. The prevalence of air conditioning was measured as

proportion of household possession of an air conditioner obtained from biennial Survey on Electricity Consumption Characteristics of Appliance of Korea Power Exchange. GRDP was obtained from Regional Income published by Statistics Korea. A medical index was calculated using data obtained from National Health Insurance Service. It consisted of the number of hospitals, hospital beds, and medical personnel (per 10,000 people for each item). These three indicators are widely used to indicate medical resources. Each of number was z-scored, and z-scored values were summed, with a higher value of the medical index indicating that medical resources were more well-established. To decompose city characteristics into spatial and temporal scale, we group-centered city characteristic variables. First, we calculated city-specific average of this variable for 16 years (i.e. city mean) (CM_variable name). We then subtract this city mean from corresponding period-specific variables (i.e. centered) (CEN_variable name). For example, suppose values of variable A in City 1 were 10 in 1998–2005 and 20 in 2006–2013. CM_Variable A was the mean value of these two ($(10 + 20) / 2 = 15$). CEN_Variable A was the difference between original values and CM_Variable A: $15–20 = -5$ in 1998–2005 and $20–15 = 5$ in 2006–2013 [Table 1]. City mean variables and centered variables were used to indicate spatial and temporal characteristics, respectively. This centering technique has been widely used in multilevel analysis (Hox et al., 2017).

I_R^2 for intercepts in multivariate meta-analysis were calculated to see the proportion of variance due to τ^2 (between-city and time period variance) after being explained by meta-predictors (Jackson et al., 2012).

We used best linear unbiased prediction (BLUP) from a meta-regression model to obtain city-and time period-specific cumulative associations between temperature and mortality. BLUP incorporates information of city- and time period-specific estimates in the first-stage analysis and that of pooled estimates in the second-stage analysis. Thus, we allowed cities (and periods) with smaller number of cases to borrow information from those with similar characteristics and larger number of cases (Gasparrini et al., 2012). The assumption for the use of BLUP is that cities with similar characteristics for one of the two eight-year time periods have similar effects of temperature on mortality.

As sensitivity analysis, we also conducted time-series analysis using cubic B-spline of time variable with 10 dfs/year to adjust for temporal trend instead of the time-stratified case-crossover analysis. We also repeated the main analysis for four consecutive periods (1998–2001, 2002–2005, 2006–2009 and 2010–2013).

3. Results

Table 2 presents all-cause mortality cases in seven major South Korean cities for 1998–2005 and 2006–2013. There were 656,135 and 701,266 all-cause mortality cases in 1998–2005 and 2006–2013, respectively. Seoul contributed the largest to total cases while Ulsan had the lowest portion. Cardiovascular and respiratory mortality accounted for approximately 27% and 7% of all-cause mortality, respectively.

Fig. 1 displays temperature distribution in the seven cities for 1998–2005 and 2006–2013. Median temperatures for these two time periods were 14.6 °C and 14.2 °C in Seoul, 15.8 °C and 15.9 °C in Busan, 14.0 °C and 13.7 °C in Incheon, 15.5 °C and 15.7 °C in Daegu, 15.2 °C, and 15.4 °C in Gwangju, 14.3 °C and 14.1 °C in Daejeon, and 15.4 °C and 15.1 °C in Ulsan, respectively. Fig. 2 shows average temperature and standard deviation of temperature in all seven cities. Average temperatures for 1998–2005 and 2006–2013 were 13.0 °C and 12.7 °C in Seoul, 14.9 °C and 15.0 °C in Busan, 12.7 °C and 12.4 °C in Incheon, 14.4 °C and 14.6 °C in Daegu, 14.0 °C and 14.3 °C in Gwangju, 13.2 °C and 12.9 °C in Daejeon, and 14.6 °C and 14.3 °C in Ulsan, respectively. When looking into annual average temperature, it fluctuated over time in five of the cities while it decreased over time in two cities (Seoul and Incheon, p-value for linear trend ≤0.05) [Fig. S1]. Standard deviation of temperature increased from 1998–2005 to 2006–2013 in all seven cities [Fig. 2]. Annual standard deviation of temperature also increased in the six cities (p-value for linear trend ≤0.05) except for Incheon (p-value for linear trend = 0.227) [result not shown here].

Fig. 2 also provides variation in city- and time period-specific characteristics including the prevalence of air conditioning, the proportion of those aged 65+, GRDP, the medical index and population density. The prevalence of air conditioning increased from 1998–2005 to 2006–2013, with Daegu having the highest prevalence. Trends for the proportion of those aged 65+ showed that all seven cities experienced population aging. Based on GRDP reflecting South Korean economy growth, Ulsan had economic superiority compared to the other cities, with relatively younger population. This is because Ulsan is the greatest industrial city in South Korea. The medical index of all seven cities was improved, with Gwangju and Daejeon taking the lead in the medical index. Population density of all seven cities rarely changed while Seoul was an extremely dense city compared to the other six cities.

Fig. 3 shows Pearson correlation matrix for city- and time period-specific characteristics of the seven cities for 1998–2005 and 2006–2013. Since these characteristics were centered by city mean values, city mean values of characteristics (prefix CM) and city mean-centered values of characteristics (prefix CEN) were not correlated with each other. Since the prevalence of air conditioning, the proportion of those aged 65+, GRDP, the medical index and standard deviation of temperature increased from 1998–2005 to 2006–2013 in all of the seven cities [Fig. 2], they (CEN_variable name) were highly correlated

Table 1
An example of group (i.e. city)-centering of variable A. CM_Variable A and CEN_Variable A denote city mean variable A and city-centered variable A, respectively.

City	Period	Variable A	CM_Variable A	CEN_Variable A
City 1	1998–2005	10	15	−5
City 1	2006–2013	20	15	+5
City 2	1998–2005	25	26	−1
City 2	2006–2013	27	26	+1
…	…	…	…	…

The ellipsis indicates that the contents of the table can be extended to several cities.

Table 2
All-cause mortality cases in seven major South Korean cities for 1998–2005 and 2006–2013.

	1998–2005		2006–2013	
	Total	Daily mean	Total	Daily mean
All-cause				
Seoul	271,243	92.8	280,970	96.2
Busan	129,955	44.5	139,207	47.6
Incheon	68,420	23.4	77,733	26.6
Daegu	79,636	27.3	83,923	28.7
Gwangju	40,541	13.9	44,506	15.2
Daejeon	39,603	13.6	43,184	14.8
Ulsan	26,737	9.2	31,743	10.9
All 7 cities	656,135	224.5	701,266	240.0
Cardiovascular				
Seoul	74,212	25.4	66,170	22.6
Busan	41,849	14.3	41,451	14.2
Incheon	20,021	6.9	21,262	7.3
Daegu	21,001	7.2	22,804	7.8
Gwangju	9243	3.2	10,228	3.5
Daejeon	10,554	3.6	10,773	3.7
Ulsan	7320	2.5	8628	3.0
All 7 cities	184,200	63.1	181,376	62.1
Respiratory				
Seoul	16,493	5.6	18,428	6.3
Busan	7321	2.5	10,761	3.7
Incheon	4362	1.5	6031	2.1
Daegu	5003	1.7	6331	2.2
Gwangju	2378	0.8	3879	1.3
Daejeon	2726	0.9	3473	1.2
Ulsan	1831	0.6	2631	0.9
All 7 cities	40,114	13.6	51,534	17.7

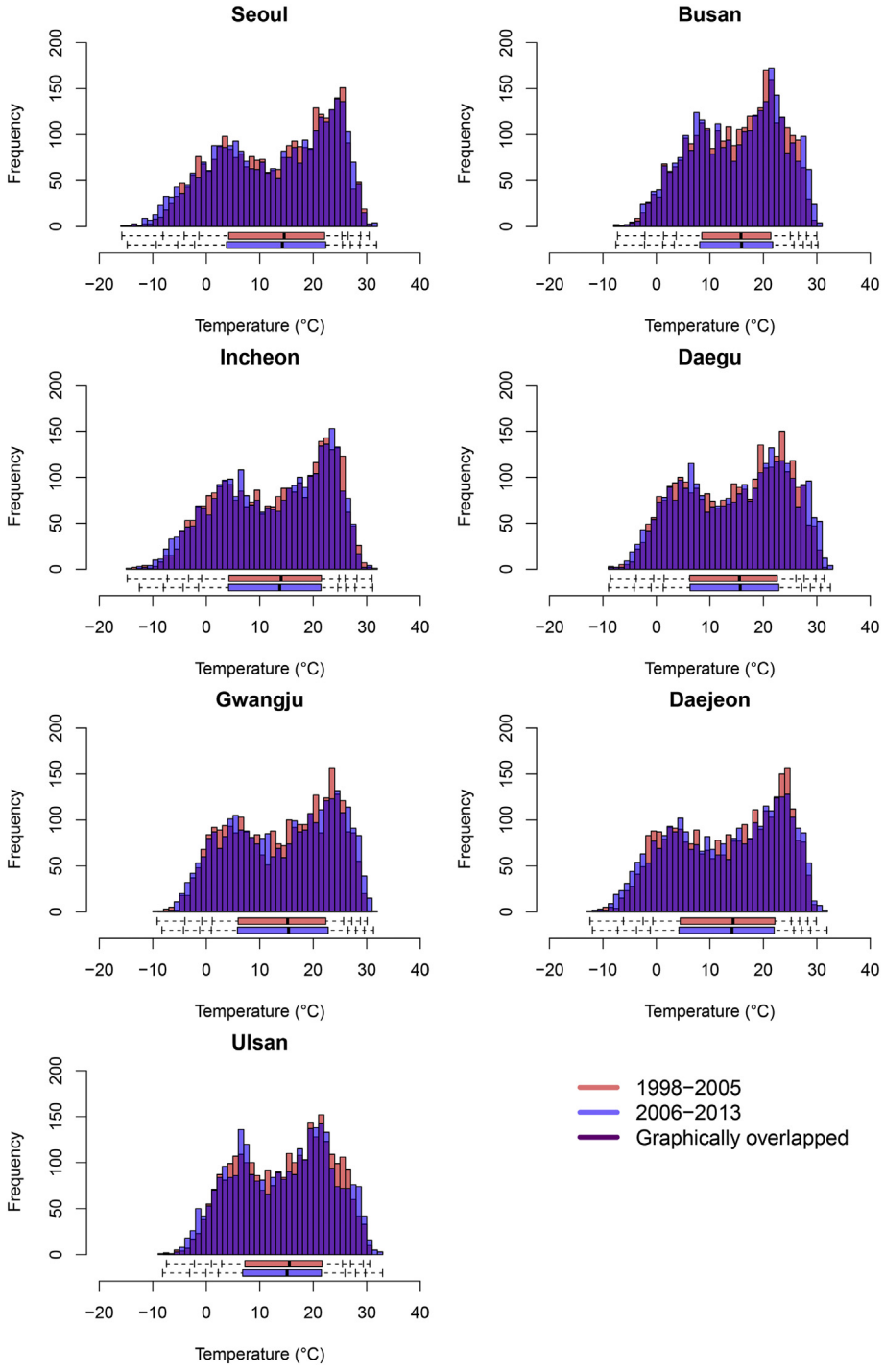

Fig. 1. Temperature distribution of seven major South Korean cities for 1998–2005 and 2006–2013. Whiskers left to boxes denotes the minimum, 1st, 5th and 10th percentile temperature respectively. Whiskers right to boxes denotes 90th, 95th, 99th percentile, and the maximum temperature, respectively.

with each other ($r = 0.81$–0.97). When looking into city mean values of characteristics, average temperature and standard deviation of temperature (CM_variable name) were highly correlated ($r = -0.86$). GRDP and proportion of those aged 65+ was also highly correlated ($r = -0.80$).

Results of multivariate meta-regression on cumulative association between temperature and all-cause mortality in the seven cities for 1998–2005 and 2006–2013 are presented in Table 3. When a dummy variable for the period of 2006–2013 were used in a multivariate meta-regression, I^2_R decreased from 21.2% to 15.6%. Variation in cumulative association of temperature and all-cause mortality between the period of 1998–2005 and 2006–2013 is shown in the first panel of Fig. 4. Within moderate cold temperature range (approximately 10th and 75th percentile of temperature), cumulative relative risks (CRRs) decreased from 1998–2005 to 2006–2013.

Dummy variables for city level did not explain the heterogeneity of cumulative association between temperature and mortality [Table 3]. This might be because cities with similar city characteristics might have similar cumulative associations. Thus, dummy variables for city level might not sufficiently distinguish city characteristics related with spatial variation in the cumulative associations. When we considered city characteristics variables such as standard deviation, and average

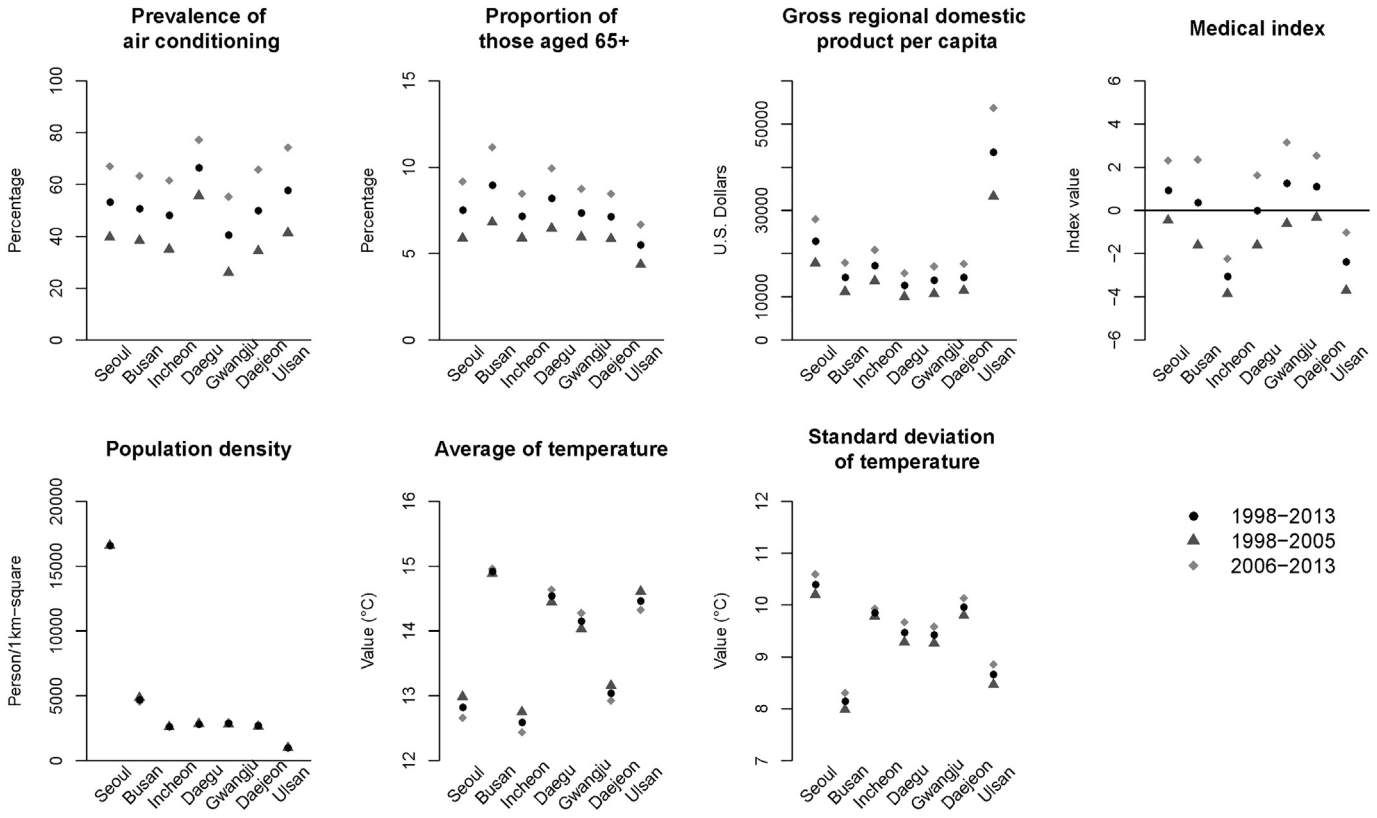

Fig. 2. City- and time period-specific characteristics of seven major South Korean cities.

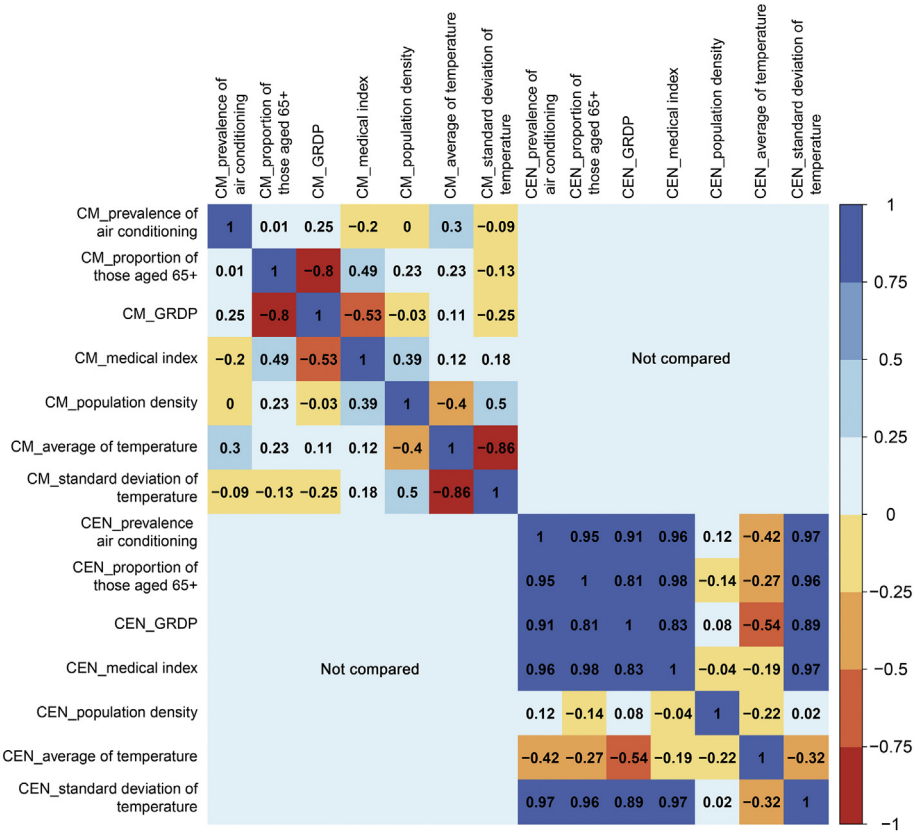

Fig. 3. Pearson correlation matrix of city- and time period-specific characteristics for seven major South Korean cities during 1998–2005 and 2006–2013. City mean (CM) variables and city mean-centered (CEN) variables were used. GRDP refer to gross regional domestic product per capita.

Table 3
Results of multivariate meta-regression for the cumulative association between temperature and all-cause mortality in seven major South Korean cities for 1998–2005 and 2006–2013.

Multivariate meta-regression model		Likelihood ratio test	Wald's test
	I^2_R (%)	*p*-Value	*p*-Value
No predictor	21.2	–	–
Single meta-predictor			
City	36.3	0.943	0.821
Period	15.6	0.140	0.119
CM_prevelance of air conditioning	16.2	0.517	0.511
CM_proportion of those aged 65+	15.8	0.727	0.647
CM_GRDP per capita	15.4	0.990	0.988
CM_medical index	21.9	0.796	0.786
CM_population density	17.7	0.668	0.561
CM_average of temperature	16.2	0.299	0.074
CM_standard deviation of temperature	12.4	0.188	0.043
CEN_prevelance of air conditioning	16.9	0.140	0.118
CEN_proportion of those aged 65+	16.8	0.138	0.119
CEN_GRDP per capita	16.9	0.242	0.204
CEN_medical index	16.8	0.154	0.139
CEN_population density	17.9	0.761	0.729
CEN_average temperature	14.8	0.085	0.044
CEN_standard deviation of temperature	17.2	0.244	0.212
Multiple meta-predictors			
CM_standard deviation of temperature + CEN_medical index + CEN_average of temperature	0	0.045	0.010

*CM, city mean; CEN, city mean-centered; GRDP, gross regional domestic product per capita.

temperature, we found that the cumulative association differed across cities. For example, with CM_standard deviation of temperature included in a multivariate meta-regression model, I^2 decreased from 21.2% to 12.4%. Corresponding *p*-value for likelihood ratio test and Wald's test was 0.188 and 0.043 respectively. For temporal variation of CRRs from 1998–2005 to 2006–2013, inclusion of CEN_prevalence of air conditioning, CEN_proportion of those aged 65+, or CEN_medical index showed *p*-values of 0.138–0.154 and 0.118–0.139 in likelihood ratio test and Wald's test, respectively. Since these variables were highly correlated with each other [Fig. 3], we selected CEN_medical index for multivariate meta-regression with multiple variables because variation by CEN_medical index was consistent with a priori knowledge about its impact on variation (i.e. improvement in medical resources may decrease temperature-related mortality), but not the other two (i.e. older population may be more susceptible to temperature and increase in the use of air conditioning may decrease heat-related mortality) (Arbuthnott et al., 2016; Sheridan and Allen, 2018). Temporal patterns of CRRs by CEN_prevalence of air conditioning, CEN_proportion of those aged 65+, and CEN_medical index were similar [Fig. S2]. In addition, CEN_average of temperature was also associated with temporal variation of CRRs. *p*-Value in likelihood ratio test and Wald's test was 0.085 and 0.044, respectively.

When CEN_average of temperature, CM_standard deviation of temperature, and CEN_medical index were all included in a meta-regression model, I^2_R decreased from 21.2% to 0%. *p*-Values in likelihood ratio test and Wald's test in comparison to a meta-analytic model without any variable were 0.045 and 0.010, respectively [Table 3].

The second, third, and fourth panels of Fig. 4 present spatial variation in CRRs by CM_standard deviation of temperature, temporal variation in CRRs by CEN_average of temperature, and temporal variation in CRRs by CEN_medical index, respectively. This figure shows CRRs at 25th and 75th percentile of one meta-predictor while the other predictors were set to 50th percentile. At 75th percentile of CM_standard deviation of temperature, CRRs in heat temperature range (above minimum mortality temperature, MMT) was higher than those at the 25th percentile: MMT is the temperature when mortality rate is the minimum. Meanwhile, at 75th percentile of CEN_average temperature, CRRs in heat temperature range was lower than those at the 25th percentile. CRRs in moderate cold temperature range (approximately between 10th and 75th percentile of temperature) was lower at 75th percentile of CEN_medical index compared to those at the 25th percentile. When different percentiles of these three meta-predictors were analyzed, CRRs in heat temperature range and moderate cold temperature range were monotonically associated with them [Fig. S3].

Fig. 5 depicts different temporal variation in cumulative association between temperature and all-cause mortality across the seven cities. While CRRs in moderate cold temperature range decreased from 1998–2005 to 2006–2013, temporal variation of CRRs in heat temperature range differed across cities. CRRs in heat temperature range in Busan, Daegu and Gwangju decreased from 1998–2005 to 2006–2013. On the contrary, these CRRs increased in Incheon. Seoul and Ulsan did not have changes in these CRRs. CRRs in heat temperature range were relatively stronger in colder cities (also more variable temperature) such as Seoul, Incheon, and Daejeon during 2006–2013 [See average and standard deviation of temperature in Fig. 3]. MMTs for 1998–2005 and 2006–2013 changed in Incheon, Daegu and Gwangju only (See confidence intervals of CRRs between 1998–2005 and 2006–2013 were not overlapped around MMT in Fig. 5). MMT changed from 26.0 °C (95.1st) to 25.3 °C (93.0th) in Incheon, from 27.1 °C (93.2nd) to 27.7 °C (93.6th) in Daegu, and from 26.4 °C (93.1st) to 27.2 °C (92.7th) respectively.

Fig. 6 shows an x-axis transformed version of Fig. 5. City- and time period-specific temperature percentile was used for x-axis in Fig. 6 because city-specific temperature percentile slightly changed from 1998–2005 to 2006–2013 [Fig. 1]. Y-axis was also changed to percentage increase which was CRR minus 1 multiplied by 100. Overall patterns of Figs. 5 and 6 were similar. By comparing mortality risk at 99th percentile of temperature to the risk at minimum mortality temperature, percentage increase of mortality risk decreased from 1998–2005 to

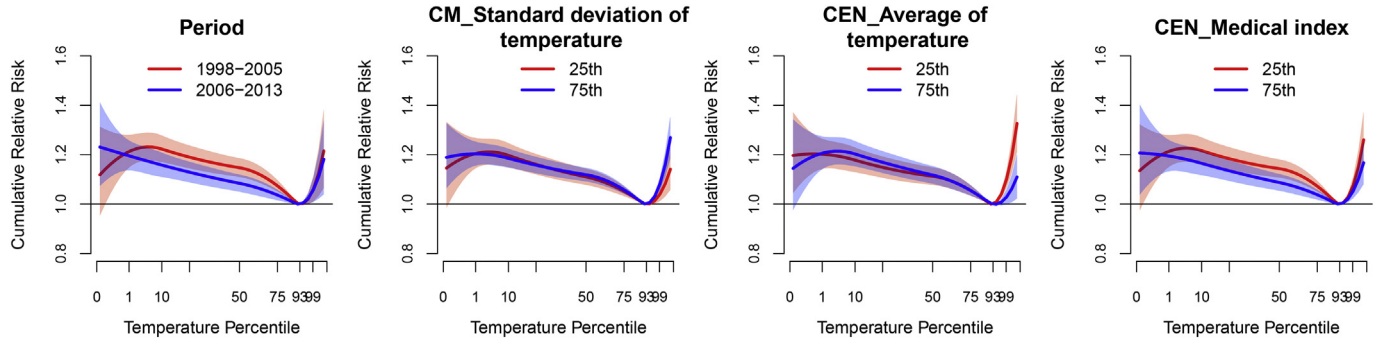

Fig. 4. Variation in cumulative association between temperature and all-cause mortality in seven major South Korean cities for 1998–2013. CM and CEN denote city mean and city mean-centered variable, respectively.

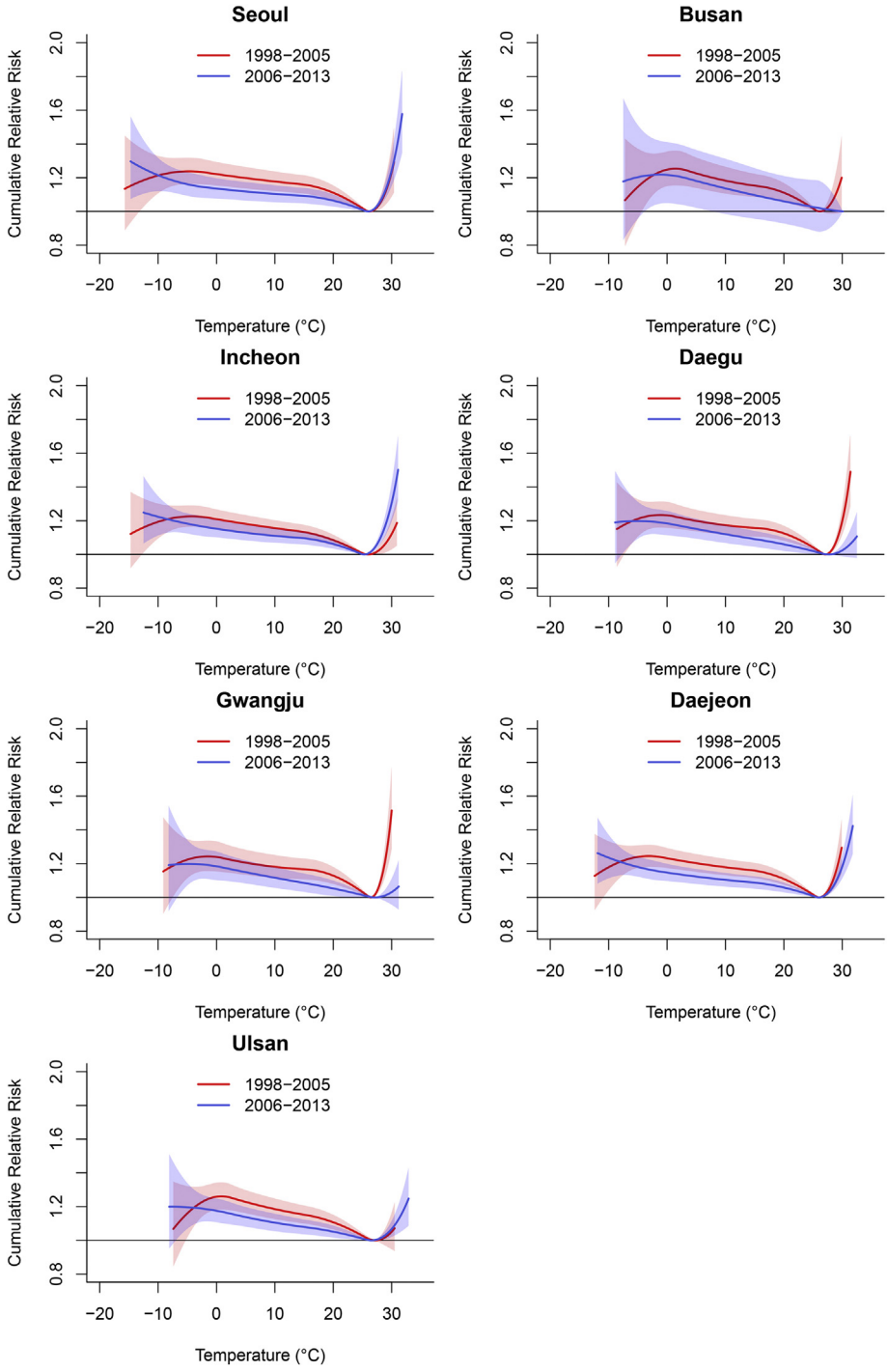

Fig. 5. Spatiotemporal variation in cumulative association between temperature and all-cause mortality in seven major South Korean cities.

2006–2013 in Busan, Daegu, and Gwangju: from 4.8% (95% CI: −1.3, 11.3) to 0.4% (95% CI: −6.0, 7.4) in Busan, from 17.2% (95% CI: 10.2, 24.7) to 4.0% (95% CI: −1.4, 9.8) in Daegu, and from 20.3% (95% CI: 11.5, 29.7) to 2.2% (95% CI: −3.5, 8.3) in Gwangju. On the contrary, percentage increase of mortality risk increased from 1998–2005 to 2006–2013 in Incheon: from 3.5% (95% CI: 0.2, 6.8) to 7.9% (95% CI: 5.0, 10.9). In Seoul, Daejeon, and Ulsan, percentage increase of mortality risk did not change: from 10.8% (95% CI: 3.6, 18.5) to 10.6% (95% CI: 6.5, 14.9) in Seoul, from 9.3% (95% CI: 4.1, 14.6) to 8.7% (95% CI: 5.3, 12.3) in Daejeon, and from 3.0% (95% CI: −4.0, 10.6) to 5.7% (95% CI: 1.7, 9.9) in Ulsan.

As shown in Figs. 3 and 5, cities with higher average temperature experienced increase in heat effects from 1998–2005 to 2006–2013. In this regard, we conducted multivariate meta-regression with a dummy variable for the period of 2006–2013 and CM_average temperature variable with interaction term of these two. We found that CRRs in heat temperature range were lower during the period of 2006–2013 than those during the period of 1998–2005 at 75th percentile of CM_average temperature. On the contrary, CRRs in heat temperature range for 2006–2013 were higher than those for 1998–2005 at the 25th percentile [Fig. S4]. *p*-Value in likelihood ratio test and Wald's test compared

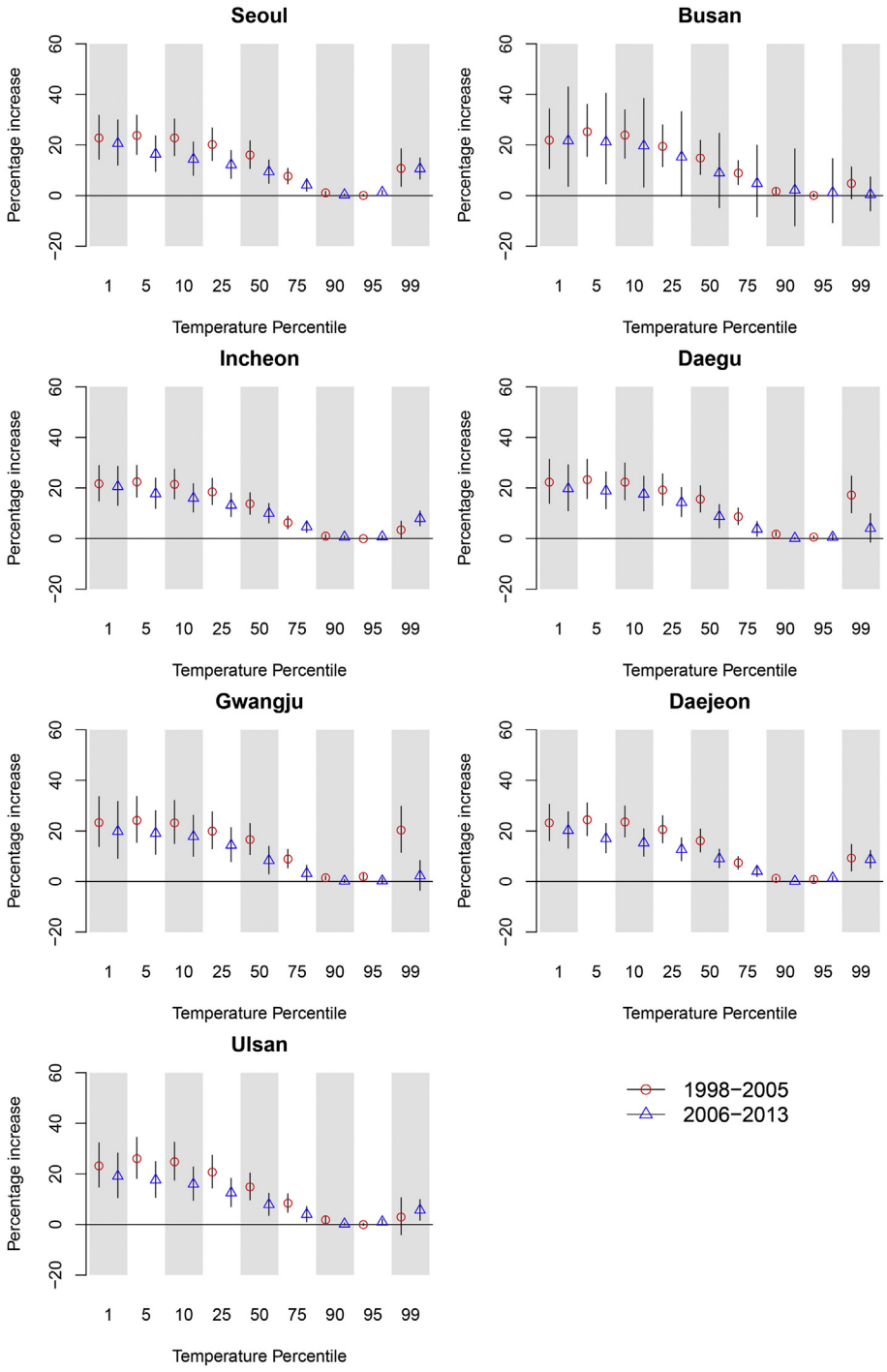

Fig. 6. Spatiotemporal variation in cumulative association between city and period-specific temperature percentiles and all-cause mortality in seven major South Korean cities.

to a meta-analytic model without any predictor was 0.156 and 0.043 respectively. I^2_R decreased from 21.2% to 0%.

In sensitivity analysis, we considered a lag-structure of temperature up to 21, and 28 days as well. We found that the cumulative associations between temperature and all-cause mortality in the first-stage analysis were consistent, and confidence intervals of the cumulative associations up to previous 21 and 28 days were much wider [Fig. S5]. Fig. S6 presents city-specific temperature-lag-mortality relationship obtained from the first-stage analysis. We also conducted time-series analysis using cubic B-spline of time variable with 10 dfs/year to adjust for temporal trend. City-specific associations between temperature and mortality obtained from the time-series analysis were generally similar to those estimated from the main analysis [Fig. S7]. Even though point estimates of CRRs in moderate cold temperature were slightly lower in the time-series analysis, confidence intervals of the main analysis and the time-series analysis were considerably overlapped.

We also repeated the main analysis for four consecutive periods (1998–2001, 2002–2005, 2006–2009 and 2010–2013). We found that consistent results for CEN_average temperature, CEN_medical index and CM_standard deviation of temperature [Fig. S8].

For cardiopulmonary mortality, cardiovascular mortality and respiratory mortality, we found inconsistent results over lag models with

different lag length. Point estimates were different and confidence intervals were very large [results not shown]. This might be due to limited statistical power and precision in our study.

4. Discussion

We found that the dose-response relationship between ambient temperature and mortality differed across cities and time in seven major South Korean cities during the period of 1998–2013. Within heat temperature range (above MMT), there were heterogeneous temporal trends over cities. In Busan, Daegu, and Gwangju, heat effect decreased from 1998–2005 to 2006–2013 while it increased in Incheon. In Seoul, Daejeon, and Ulsan, heat effect did not change. The heat effect was relatively stronger in Seoul, Incheon, and Daejeon during the period of 2006–2013 whose temperatures were lower and more variable throughout the study period than those in the other cities. Within moderate cold temperature range (approximately 10th and 75th percentile of temperature), cold effects decreased from 1998–2005 to 2006–2013. This decrease was associated with improvement of medical resources (measured as a medical index composed of three indicators: the number of hospitals per capita, and the number of hospital beds per capita, the number of medical personnel per capita) over time in all seven cities.

In South Korea, there have been efforts to enhance population adaptation to temperature nationwide. Comprehensive plans for tackling heat wave were established by NEM in 2005. The Korean Meteorological Administration then launched heat wave warning system in 2008. Fig. 7 presents that the frequency of heat wave warning from an official record of the Korean Meteorological Administration was the highest in Daegu, followed that in Ulsan and Gwangju. In our study, the heat effect decreased from 1998–2005 to 2006–2013 in Daegu, Busan, and Gwangju, but not in Ulsan. This may indicate that not only heat wave warning system, but also other factors are associated with temporal variation in the heat effect. For example, Ulsan is the largest industrial city in South Korea, where many workers may get exposed to heat in workplaces, particularly for outdoor workers. A report issued by Ulsan Development Institute pointed out that outbreaks of heat illness in workers stand out compared to those of the whole country (UDI, 2017).

A novelty of the findings of this study is that change in heat effect was negatively associated with change in the first decimal place of average temperature albeit average temperature did not vary systematically but rather fluctuated over time in most of the cities. The result was consistent when we conducted sensitivity analysis for four consecutive periods (1998–2001, 2002–2005, 2006–2009 and 2010–2013). The negative association between average temperature and heat effect suggests that people may react to heat in short-term time scale. This finding

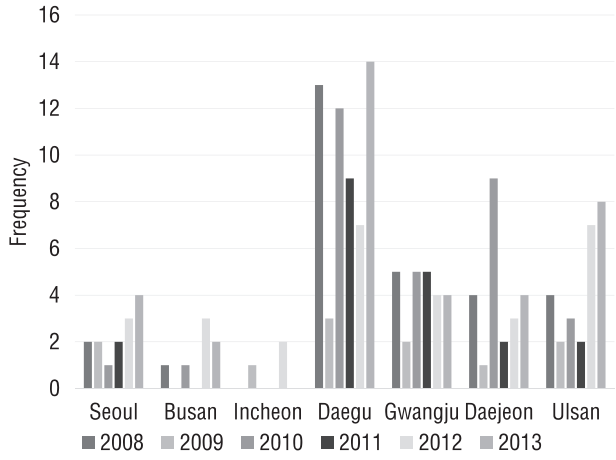

Fig. 7. The frequency of heat wave (i.e. daily maximum temperature over 33 °C) in seven major cities of South Korea during 2008–2013.

may reconcile behavioral adaptation through conscious behavior to avoid heat exposure and physiological acclimatization (Sawka et al., 2002) while physiological acclimatization to heat is not everlasting (Minett et al., 2016). In addition, we found that heat effect decreased from 1998–2005 to 2006–2013 in cities where average temperature for 1998–2013 was higher. We speculate that populations living in hotter cities (i.e. average temperature in summer is higher) such as those of Daegu and Gwangju might have behaved more favorably to avoid exposure to heat. People in Busan which had higher average temperature in winter season might be less susceptible to heat due to less variable weather.

The results with regard to heat effect implies that population in the future may be, to some extent, adapted to (projected) increase in temperature. However, not only average temperature but also variation of temperature which may also vary in the future seem to be related with variation in heat effects. Even though we did not find association between temporal increase in standard deviation of temperature and heat effect, we found positive association between standard deviation of temperature and heat effect in spatial scale. A previous study also reported that cities with more variable temperature in summer season were more susceptible to heat effect in 50 cities of the United States (Medina-Ramón and Schwartz, 2007). Further studies are needed to identify the impact of heat effect on human health in climate change, taking into account relationships of change in average temperature and variation of temperature with temperature-health outcome curves.

We found that improvement in medical resources might be associated with mortality risk in moderately cold temperature range. In this temperature range, vulnerable individuals might have contributed more to mortality risk. General improvement in medical services and qualities might have been effective in reducing mortality risk for susceptible people. On the contrary, we did not find association between spatial difference in the medical index and mortality risk. Spatial difference in the medical index might have different meanings. Difference in medical resources across cities might not have been enough to make a difference in the effect of temperature on mortality. When we used each of the individual indicators, the results were consistent. Other possibility is that these indicators might not have been sufficient to capture spatial difference in medical sources. More detailed indicators may be needed to reflect varieties of medical resources across these seven metropolitan cities.

Our results were inconsistent with previous studies conducted in South Korea. Lee et al. (2018b) reported decrease in heat effect for all seven cities during the period of 1992–2010. The big difference compared to their study is the study period. Notably, in 1994, there was historical heat wave throughout South Korea (Kyselý and Kim, 2009). This heat wave might have made a big difference in adaptation to heat. Chung et al. (2017) investigated annual variation in heat effect using the same period of Lee et al. (2018b) excluding Ulsan. They found that the heat effect decreased by the end of 1990s and fluctuated in 2000s while the prevalence of air conditioning increased over time. Thus, the prevalence of air conditioning might have contributed to the decrease in the early period. However, in our study, temporal variation in heat effect differed across cities although the prevalence of air conditioning continued to increase over time. Our results imply that mechanism of variation in heat effect may be complex. Heo et al. (2016) also found that temporal variation in heat effect differed across regional climate. Their study found that heat effect increased in the hottest clusters during the period of 2008–2012 compared to that during the period of 1996–2000. However, their study sites were all administrative units in South Korea. In addition, they considered lag effects up to previous 7 days of exposure only, and reported the strongest estimates among individual lag days, not the cumulative estimate, making it difficult to compare with our results (note that we found prolonged lag effects of heat temperature and the cumulative effect differing from the strongest effect among lag days [Fig. S6]). Meanwhile, Kim et al. (2015) have shown that temporal variation in temperature effect may vary by

cardiovascular, cerebrovascular and respiratory mortality in Seoul during the period of 1995–2011. However, in this study, we could not identify temporal variation in such cause-specific mortality.

This study has several limitations. First, we did not consider intra- or inter-variation of daily temperature which might be important factors to predict temperature-related mortality (Vicedo-Cabrera et al., 2016). A multi-city study on diurnal temperature range (i.e. difference between daily maximum and minimum temperature) showed increasing pattern in pooled effect of diurnal temperature range on mortality in South Korea during the period of 1992–2010 (Lee et al., 2018a). Since health effects of temperature may be combinations of those effects, our results may reflect partial entity of temperature-related mortality risk. Nevertheless, evaluation on the relationship between daily mean temperature and mortality may provide important public health implication on temperature risks, particularly by investigating its spatiotemporally varying nature, including adaptation and vulnerability factors. Second, we did not consider variables for heat waves or cold spells. Nevertheless, our models might have reflected such prolonged temperature risks. Previous investigations on relationship between non-linearity of temperature and definitions of heat wave and cold spells showed that effects at extreme temperature percentile might reflect effects of heat wave and cold spells (Hajat et al., 2006). Third, we failed to find spatial or temporal variation in the temperature effect on cardiopulmonary, cardiovascular and respiratory mortality. We found that point estimates and confidence intervals were unstable in different models and analyses. This might be due to lack of statistical power and precision. To address this, we are currently performing the same analysis using extended datasets for 65 cities in South Korea.

In this study, we did not identify attributable fraction or number (AF, AN) to temperature (Gasparrini and Leone, 2014). These measures indicate actual fraction and number cases attributable to temperature. AF and AN depend on not only RR, but also depend on the frequency and the strength of heat and cold days (also the number of event cases in AN). We believe that changes in RR at identical absolute and percentile scale of exposure are more appropriate for studying the adaptation to temperature. This is because when AF/AN is used, temporal changes in a slope factor in the temperature-mortality relationship may be masked by temporal changes in the frequency and the strength of heat and cold temperature. The frequency and the strength of heat and cold temperature are related to mitigation strategies rather than to adaptation strategies. Thus, AF, AN, and RR are all instructive measures, although implications of each measures can differ by viewpoints of research. AF and AN can be useful for prediction of actual fraction and number of cases attributable to temperature in the past and in the future (e.g. health impact assessment). This prediction is not the scope of this study.

5. Conclusion

In this study, we found difference in temporal variation of temperature-related mortality risk in seven metropolitan cities of South Korea in 1998–2013. Heat effect was found to be decreased in three cities with higher average temperature (Busan, Daegu, Gwangju) from 1998–2005 to 2006–2013, but not in Ulsan. Meanwhile, in relatively colder cities, heat effect did not change (in Seoul and Daejeon) or increased from 1998–2005 to 2006–2013 (in Incheon). Change in heat effect was negatively associated with change in average temperature albeit average temperature did not vary systematically in most of the cities. This implies that population may response to heat in short-term time scale. General improvement in medical resources might have reduced temperature-related mortality risk in moderate cold temperature range. This study provides implications that adaptation plans for temperature-related risks should differ across populations considering the fact that adaptation to temperature may differ across populations and within the same population over different time periods.

Description of conflicts of interest

There is no conflict of interest relevant to this study to disclose.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.11.210.

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